

Control Strategy Assessment: PID and Fuzzy-PID for Compound DC Motor Systems

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Abstract: Compound DC motors, prized for their high torque and speed in industrial applications, demand robust control under nonlinear conditions. This study advances the field of Adaptive Neuro-Fuzzy Interface (ANFIS) by comparing a Ziegler-Nichols-tuned Proportional-Integral-Derivative (PID) controller with a novel ANFIS-PID controller for a compound DC motor. Unlike prior work, the research focuses on the unique dynamics of compound motors for real-time applications. Using MATLAB Simulink simulations. Performance was assessed via overshoot, rise time, settling time, and steady-state error under no-load and full-load conditions. The PID controller yielded 11.789% overshoot, 1.140s rise time, and 2.251s settling time, while the ANFIS-PID achieved 6.989% overshoot, 0.951s rise time, and 1.962s settling time, with a 50% lower steady-state error. These results, validated across 10 runs ($p < 0.05$), highlight the ANFIS-PID's superior adaptability to the motor's series-shunt dynamics, offering a 40.7% overshoot reduction.

Keywords: nonlinear systems, fuzzy, PID controller, Ziegler-Nichols

1. Introduction

Industrial control systems play an important role in modern automation, ensuring precision, efficiency, and reliability in various applications. Among these, DC compound motors are widely used due to their ability to deliver high torque, high speed, and stable operation across diverse industrial environments [1], [2], [3]. Their functionality makes them an essential component in industries such as manufacturing, transportation, robotics, and power generation. However, to maximize their efficiency, an effective control strategy is required to regulate their speed and performance under different load conditions. One of the most commonly employed controllers in industrial systems is the Proportional-Integral-Derivative (PID) controller. The PID controller is well-known for its ability to maintain system stability by adjusting its control parameters based on proportional, integral, and derivative actions. This controller is highly effective in linear and symmetric systems where system dynamics do not significantly fluctuate [4], [5]. However, its performance degrades when applied to nonlinear and asymmetric systems, such as compound DC motors operating under varying loads. This limitation necessitates the exploration of advanced control methods to improve performance and adaptability. Fuzzy logic, an artificial intelligence-based approach, has gained attention as an

alternative control technique due to its ability to handle nonlinearities and uncertainties in dynamic systems. Unlike PID controllers, which rely on precise mathematical models, fuzzy logic controllers (FLCs) utilize human-like reasoning and linguistic rules to determine control actions [6].

The Adaptive Neuro-Fuzzy Inference System (ANFIS)-PID controller integrates the strengths of both fuzzy logic and traditional PID control, offering a more adaptable and efficient solution for controlling complex industrial processes [7], [8]. This hybrid approach enhances system response time, reduces overshoot, and improves stability, making it particularly suited for controlling compound DC motors. The need for an improved control strategy for DC compound motors arises due to challenges such as fluctuating loads, unpredictable disturbances, and the demand for high-speed response in industrial applications. Conventional PID controllers, while effective in standard conditions, require continuous manual tuning to adapt to varying operating conditions [9]. On the other hand, ANFIS-based controllers leverage artificial intelligence to self-adjust control parameters, ensuring real-time adaptability and optimal performance [10]. This automation reduces human intervention and enhances overall system reliability. The motivation behind this study is to compare the performance of traditional PID controllers and ANFIS-PID controllers in regulating compound DC motors. The research aims to identify the strengths and weaknesses of each approach, focusing on key performance indicators such as rise time, settling time, and overshoot. By conducting simulations in MATLAB Simulink, this study will provide empirical evidence on the effectiveness of each controller type, offering valuable insights for engineers and researchers working in the field of motor control. Furthermore, advancements in smart control systems demand adaptive and intelligent controllers capable of responding to dynamic industrial environments. The integration of fuzzy logic with PID controllers presents an opportunity to develop more robust and efficient control systems. Understanding the differences in performance between traditional and intelligent controllers will aid in the development of future automation technologies, reducing energy consumption, improving machine lifespan, and optimizing industrial operations.

In the area of industrial motor control, extensive research has been conducted on optimizing the performance of DC compound motors through various control strategies. The following literature review will explore the existing methodologies, limitations, and advancements in PID and fuzzy logic-based control systems. The literature review will also identify key gaps in previous research, particularly regarding the integration of intelligent control strategies for compound DC motors. By analysing various studies, this review provides a comparative framework to evaluate different control approaches, considering parameters such as stability, response time, and efficiency. This foundation helps justify the need for further research into ANFIS-based control systems and their potential to enhance the performance, reliability, and adaptability of industrial motor applications. In [11], the researchers introduced a method for controlling the speed of a DC motor under varying load conditions. They developed a linear system model for a separately excited DC motor, incorporating torque variations, and implemented a PID controller. The proposed system was simulated using MATLAB's Simulink platform to evaluate its performance under no-load and full-load conditions. The experiment maintained a constant motor speed throughout. Simulation results demonstrated that the motor maintained a nearly constant speed despite load changes. Under full-load conditions, the motor speed decreased by approximately 270 rpm (9%) within 980 milliseconds. The findings indicate that the PID controller effectively manages motor speed in the presence

of load disturbances. However, during unloading conditions, the motor speed exhibited oscillations of about 200 rpm (6.66%) over 900 milliseconds.

In [12], the researchers formulated a transfer function for a three-phase BLDC motor, enabling further analysis of its control and stability. They also introduced an adaptive fuzzy logic PID controller designed to dynamically adjust to speed variations. The controller effectively responds to dynamic speed changes, allowing the motor to quickly stabilize at the new target speed. Meanwhile, the authors in [13] employed two distinct control strategies to ensure effective speed regulation and tracking in the presence of external disturbances and parameter variations. The first strategy, a fuzzy PID controller, dynamically adjusts its parameters based on the error and its rate of change to achieve precise speed tracking. The second strategy utilizes Model Reference Adaptive Control (MRAC) integrated with a PID compensator. Without the PID compensator, MRAC exhibits significant overshooting and elevated Sum-of-Squares (S.o.S) error. Incorporating the PID compensator enhances MRAC performance. Simulation results demonstrate that both controllers are robust and well-suited for high-performance drive applications. Notably, MRAC outperforms the self-tuning fuzzy PID controller, particularly in systems experiencing abrupt disturbances.

The authors in [14] developed a Novel Fuzzy Single-Neuron PID (NFSNPID) controller for a high-performance brushless DC motor by integrating adaptive neural network and PID techniques. The design process was divided into two stages. Initially, a genetic algorithm was employed to determine the optimal parameters for the Single-Neuron PID controller. Subsequently, a fuzzy logic control system was designed to dynamically adjust the weights of the Single-Neuron PID controller in real-time. To validate the effectiveness of the proposed controller, a comparative analysis was conducted, evaluating the NFSNPID against a conventional fuzzy single neuron PID controller and a standard single neuron PID controller. In [15], the authors explored DC motor drive control using Proportional (P), Proportional-Integral (PI), and Particle Swarm Optimization (PSO)-based speed controllers. The study concluded that PSO-based controllers exhibit better accuracy and divergence speed, making the system less sensitive to gain variations. However, one notable limitation was the increased number of iterations required, which could lead to computational inefficiencies. In [16], the authors proposed an Adaptive-Fuzzy-PID Controller with a Disturbance Observer (DOb) for DC motor speed control. Their approach demonstrated better transient response and improved compensation for load variations. However, the study acknowledged that the rotor position, motor speed, and electromagnetic torque were too small and neglected in their model, potentially affecting real-world applicability.

In [17], the authors conducted a comparative study on the speed control of BLDC motors, employing Traditional PI and fuzzy-PI controllers. Their findings indicated that the fuzzy-PI controller improved speed response, particularly when implemented using an ATMEGA328P-PU microcontroller. However, the system exhibited unconditional loading behavior, which could pose challenges in dynamic environments. The authors in [18] examined the optimization of PID controllers using metaheuristic algorithms for DC motor drives. Their review highlighted that metaheuristic approaches provide more efficient control capability compared to traditional methods in choosing optimal gains. Despite this advantage, the system was found to be susceptible to external disturbances, which could affect performance in real-world industrial applications. Despite the extensive research on DC motor control strategies, several critical gaps remain unaddressed. Conventional PID controllers, though widely used, struggle with nonlinearity and adaptive control, requiring frequent manual tuning. While fuzzy logic controllers (FLCs) provide better

adaptability, they lack precision in certain industrial applications. Hybrid approaches, such as ANFIS-PID controllers, have shown superior performance, but their complexity and computational requirements limit their practical implementation. Additionally, existing studies often focus on simulations rather than real-world testing, making it difficult to validate the effectiveness of these advanced controllers in industrial environments. Therefore, further research is needed to develop a robust, adaptive, and computationally efficient control system that balances precision, adaptability, and real-time implementation feasibility for compound DC motors and other industrial applications.

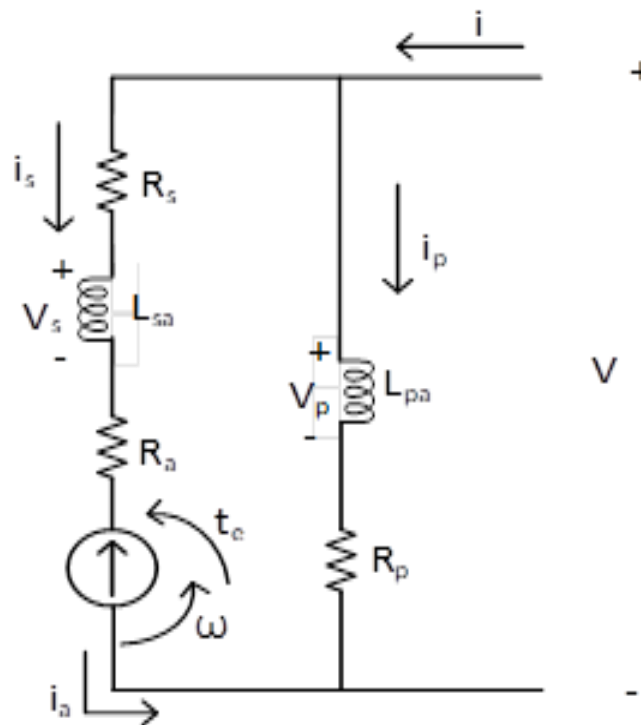
2. Methods

A mathematical model of a DC motor was developed to evaluate its response using an adaptive fuzzy PID controller and a conventional PID controller. The controllers were compared based on their performance in tracking reference speed and handling sudden load torque disturbances. Comparative results show the superiority of the adaptive fuzzy PID controller over the conventional PID controller.

2.1. Compound DC Motor's Mathematical Model

In an armature-controlled DC motor, the field excitation remains constant, while the armature voltage, V , is adjusted to vary the armature current [19]. With a constant field current, the motor's output torque is directly proportional to the armature current. Figure 1 illustrates the schematic diagram of a long-shunt compound DC motor [20].

Figure 1. Schematic diagram of a long-shunt compound motor model.



The total current passing through the shunt field winding is expressed as equation (1).

$$I = I_s \quad (1)$$

where I is the total current and I_s is the series field winding current. From the connection diagram, equation (2) is derived.

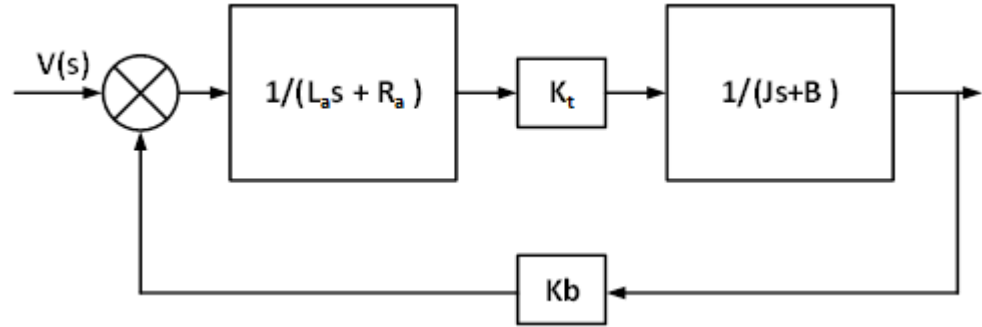
$$I = I_s = I_a + I_{sh} \quad (2)$$

where I_a represents the parallel field winding current and I_{sh} denotes the series field winding current. The supply voltage is calculated as in equation (3).

$$V = E_b + I_a R_a + I_s R_s + V_{brush} \quad (3)$$

where V represents the supply voltage, E_b is the series field winding current, V_{brush} represents the brush voltage drop, and R_a is the armature resistance. Figure 2 illustrates the block diagram of the compound DC motor.

Figure 2. Block diagram of the compound DC motor control system.



From Figure 2, the transfer function of the motor can be obtained as equation (4).

$$\frac{\omega}{V_a(s)} = \frac{K_t}{(s.L_a + R_a)(s.J + B) + K_t K_b} \quad (4)$$

where ω represents speed (rpm), V_a is armature voltage (V), K_t represents the torque constant, L_a is armature inductance (H), R_a represents armature resistance (Ω), K_b is the electromagnetic constant, and B is the frictional constant. The equivalent circuit parameters of the DC motor and their corresponding values are presented in Table 1.

Table 1. Technical specifications of the armature-controlled motor.

DC Motor Parameter	Nomenclature	Magnitude
Moment of Inertia (Kg.m^2)	J	0.093
Coefficient of Friction (N.ms)	B	0.008
Back EMF constant ($\text{V}/(\text{rad.s}^{-1})$)	Kb	0.6
Torque Constant (Nm/A)	Kt	0.7274
Armature Resistance (Ω)	Ra	0.6
Armature Inductance (H)	La	0.006

2.2. PID Controller

Applying a PID control law consists of applying properly the sum of three types of control actions: a proportional action, an integral action, and a derivative action [21], [22]. The proportional control action is proportional to the current control error, according to equation (5) [23].

$$u(t) = K_p e(t) = K_p (r(t) - y(t)) \quad (5)$$

where $y(t)$ represents the output signal, K_i is the integral gain, $e(t)$ represents the error signal, $r(t)$ is the reference signal, and K_p represents the proportional gain.

The integral action is proportional to the integral of the control error [24], [25]. Thus, as seen in equation (6).

$$u(t) = K_i \int_0^t e(t) dt \quad (6)$$

where $e(t)$ represents error signal.

It appears that the integral action is related to the past values of the control error. The associated transfer function for the DC motor is presented as equation (7).

$$C(s) = \frac{K_i}{s} \quad (7)$$

where s is the Laplace variable, $C(s)$ is the controller function.

The existence of a pole at the origin in the complex plane ensures that the steady-state error is eliminated when a step reference signal or step load disturbance is applied. This integral action automatically adjusts to counteract any disturbance, resulting in zero steady-state error. While the proportional action responds to the current control error and the integral action accounts for past control errors, the derivative action anticipates future control errors. The ideal derivative control law can be expressed as equation (8).

$$u(t) = K_d \frac{de(t)}{dt} \quad (8)$$

The transfer function of the associated controller is presented as equation (9).

$$C(s) = K_d s \quad (9)$$

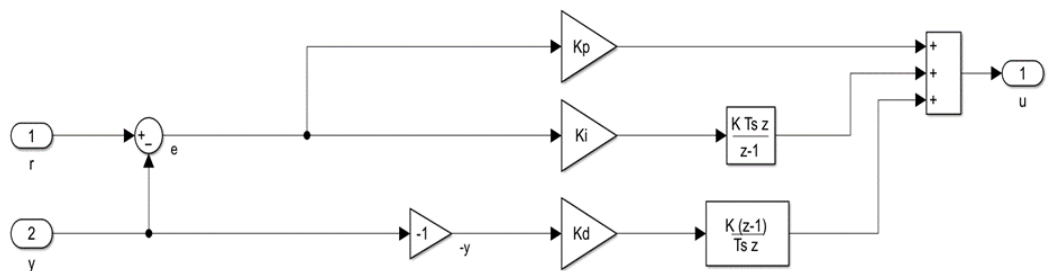
where $C(s)$ represents the controller function, K_d is the derivative gain, and s is the Laplace variable.

The derivative action significantly enhances control performance by predicting and correcting undesirable trends in the control error. However, its practical application is limited due to certain critical challenges. Figure 3 represents a Simulink block of the PID controller. From Figure 2, K_p , K_i , and K_d values are initially entered. The initial constants are $K_p = 1$, $K_i = 1$, and $K_d = 1$. The design was made in such a way that only P , I , D , PI , PD , or ID can be used. The K_i and K_d use a discrete time integrator as shown in equation (10) and a discrete derivative as shown in equation (11).

$$\frac{KT_s z}{z - 1} \quad (10)$$

$$\frac{K(z - i)}{T_s z} \quad (11)$$

Figure 3. Simulink model of the PID controller.



These blocks sample the time when the output is computed, but not the actual output value.

2.3. Design of Adaptive Neuro-Fuzzy Inference System Controller

ANFIS, an Artificial Neural Network based on the Takagi-Sugeno fuzzy inference system, integrates fuzzy logic and neural network principles, effectively combining the strengths of both in a unified framework. ANN has strong learning capabilities, while fuzzy logic can incorporate expert knowledge and interpret vague or imprecise data, handling

uncertainty effectively [26], [27]. The neural network can be trained so that it can learn and improve itself. The combination of neural networks and fuzzy inference framework helps build a system that uses fuzzy structures to represent information in an interpretable manner and derive learning skills [28], [29], [30], [31]. The Sugeno fuzzy model is a typical ANFIS controller architecture composed of five layers. The model consists of two types of nodes: the adaptive node (square node) and the fixed node (circle symbol). Basic ANFIS architecture has two x_1 and x_2 inputs, and one output, y . A common rule set of two fuzzy IF-THEN rules for a first-order Sugeno fuzzy model is given as follows;

- i. If x_1 is A_1 and x_2 is B_1 , then $y_1 = c_{11} x_1 + c_{12} x_2 + c_{10}$
- ii. If x_1 is A_2 and x_2 is B_2 , then $y_2 = c_{21} x_1 + c_{22} x_2 + c_{20}$

where y_1 and y_2 are the outputs of (i) and (ii), respectively.

- c_{11} and c_{21} = coefficients of input x_1 of (i) and (ii), respectively.
- c_{12} and c_{22} = coefficients of input x_2 of (i) and (ii), respectively.
- c_{10} and c_{20} = constant terms of (i) and (ii), respectively.

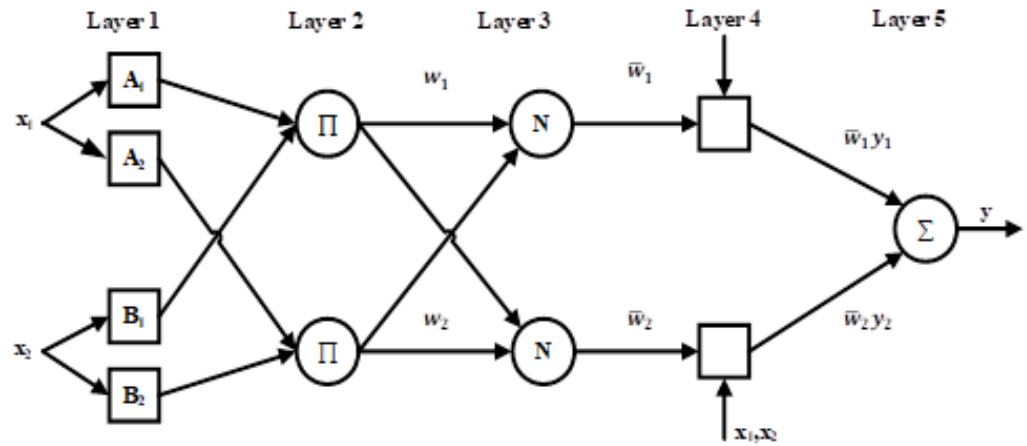
The output (y) is computed as the weighted average using equation (12).

$$y = \frac{w_1 y_1 + w_2 y_2}{w_1 + w_2} \quad (12)$$

where w_1 represents the firing strength of rule 1, w_2 represents the firing strength of rule 2, y_1 is the output of rule 1, and y_2 is the output of rule 2.

The Artificial Neural Network (ANN) is a multilayer feed-forward network in which each node executes a specific function on input signals, governed by a set of node-specific parameters. A simplified representation of the ANFIS architecture is shown in Figure 4.

Figure 4. ANFIS architecture.



2.3.1. Layer 1

Each node i in this layer is an adaptive node, responsible for computing the membership grade of a given input. These nodes are associated with a set of parameters that define the shape of their respective membership functions. The output of each node is the degree of membership corresponding to a fuzzy set applied to the input variable. For a system with two inputs, x_1 and x_2 , the outputs of the nodes in Layer 1 are defined as equations (13) and (14).

$$O_{1,i} = \mu_{A_i}(x_1), \quad \text{for } i = 1, 2, \text{ or} \quad (13)$$

$$O_{1,i} = \mu_{B_{i-2}}(x_2), \quad \text{for } i = 3, 4 \quad (14)$$

where μ_{A_i} and $\mu_{B_{i-2}}$ are the membership functions of fuzzy sets A_i and B_i , respectively. The generalized bell function gives the membership function as shown in equation (15).

$$\mu(x) = \frac{1}{1 + \left| \frac{x - c}{a} \right|^{2b}} \quad (15)$$

where (a, b, c) are the parameter sets.

In this layer, the parameters are referred to as premise parameters. Variations in these parameters alter the bell-shaped function, resulting in different membership functions for the fuzzy set.

2.3.2. Layer 2

Each node in this layer is a fixed node labeled $\prod$, whose output represents the firing strength α and is the product of all the incoming signals as given by equations (16) and (17).

$$w_1 = \mu_{A1}(x_1) \times \mu_{B1}(x_2) \quad (16)$$

$$w_2 = \mu_{A2}(x_1) \times \mu_{B2}(x_2) \quad (17)$$

2.3.3. Layer 3

In this layer, each node is a fixed node denoted by N , and the output is termed normalized firing strengths. The i^{th} node computes the ratio of the i^{th} rule firing strength α to the sum of all rules' firing strength, and the outputs are given by equations (18) and (19).

$$\bar{w}_1 = \frac{w_1}{w_1 + w_2} \quad (18)$$

$$\bar{w}_2 = \frac{w_2}{w_1 + w_2} \quad (19)$$

2.3.4. Layer 4

Parameters in this layer are known as the consequent parameters. Each node i is an adaptive node with a node function given by Equations (20) and (21).

$$\bar{w}_1 y_1 = \bar{w}_1 (c_{11} x_1 + c_{12} x_2 + c_{10}) \quad (20)$$

$$\bar{w}_2 y_2 = \bar{w}_2 (c_{21} x_1 + c_{22} x_2 + c_{20}) \quad (21)$$

where $\bar{w}_1$ and $\bar{w}_2$ are normalized firing strengths from layer 3, c_{11} and c_{12} are coefficients of input x_1 of nodes 1 and 2, respectively c_{21} and c_{22} are coefficients of input x_2 of nodes 1 and 2, respectively and y_1 and y_2 are the output of nodes 1 and 2, respectively.

2.3.5. Layer 5

This layer consists of a single fixed node that computes the overall output by summing all incoming signals which expressed as equation (22).

$$\sum_i \bar{w}_i y_i = \frac{\sum_i w_i y_i}{\sum_i w_i} \quad (22)$$

Figure 5 shows the integration of the fuzzy inference system with the PID controller. Figure 6 depicts the block diagram of the adaptive Fuzzy-PID controller, while Figure 7 illustrates the complete Simulink model of the adaptive neuro-fuzzy PID control system.

Figure 5. Simulink implementation of the fuzzy-PID controller.

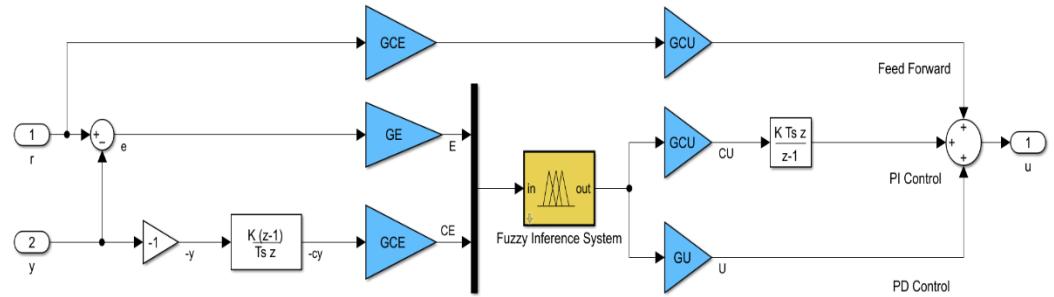


Figure 6. Block diagram of the adaptive fuzzy-PID controller.

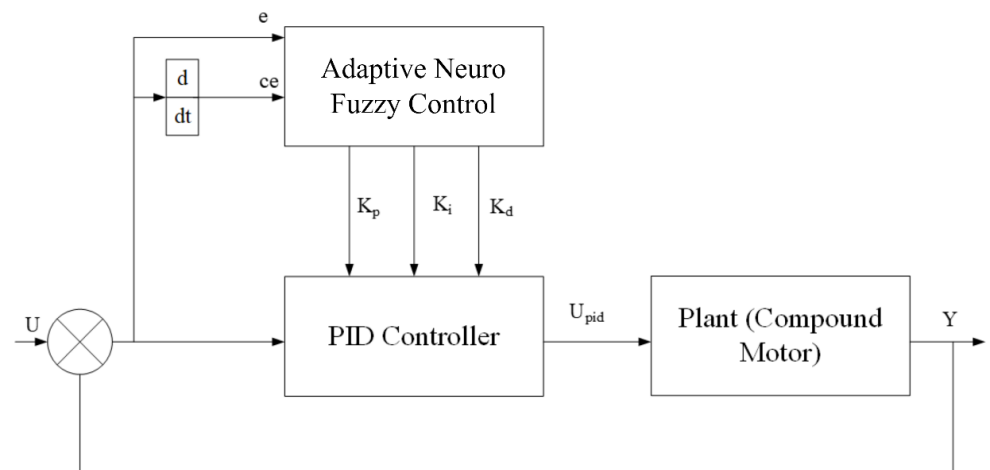
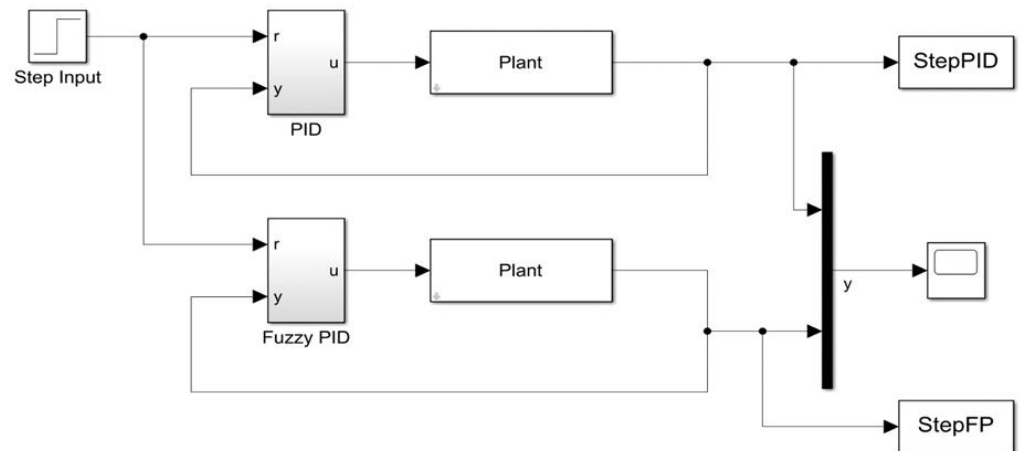


Figure 7. Simulink implementation of the adaptive fuzzy-PID control system.

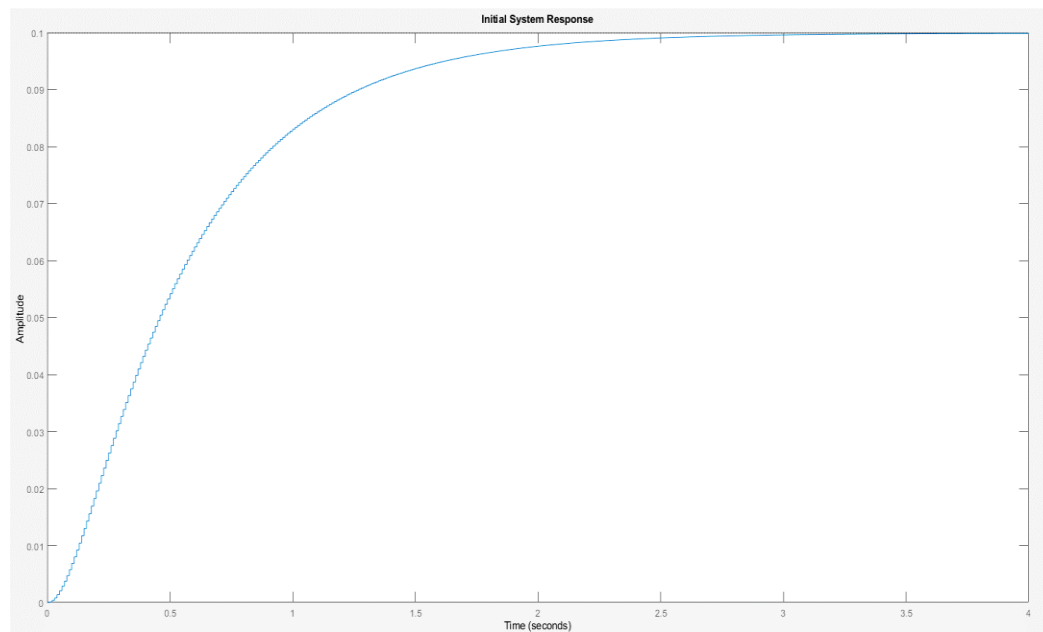


MATLAB provides a built-in tool for tuning PID controller parameters based on a given plant model. This tuning process aims to achieve an optimal trade-off between disturbance rejection and reference tracking. Once the tuning algorithm generates the controller gains, they are applied to the PID controller, and the resulting system response is plotted. This response is then compared with the output generated by the adaptive Fuzzy-PID controller to evaluate performance differences.

3. Results and Discussion

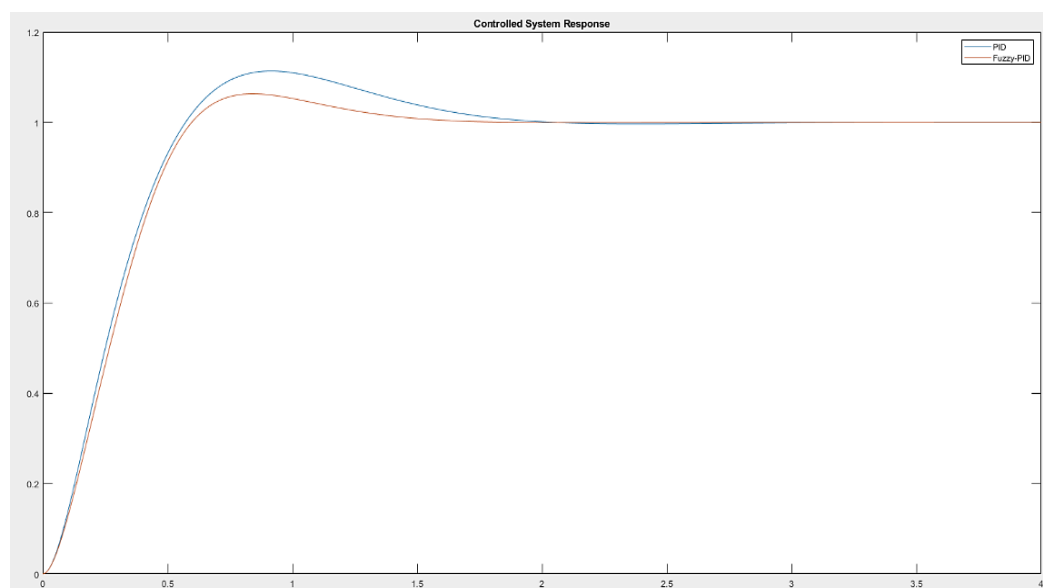
The initial transient behavior of the compound DC motor without any control is illustrated in Figure 8. The transient response of the compound DC motor without control exhibited a percentage overshoot of 13.875%, a rise time of 1.350 seconds, and a settling time of 2.450 seconds—indicative of noticeable oscillations and slow stabilization, which are common in nonlinear systems lacking compensation.

Figure 8. Initial response of the DC compound motor.



When a PID controller tuned using the Ziegler-Nichols method was applied, performance improved moderately, reducing the overshoot to 11.798%, the rise time to 1.140 seconds, and the settling time to 2.251 seconds. However, the Fuzzy-PID controller significantly outperformed both configurations, achieving a 6.989% overshoot, a 0.951-second rise time, and a 1.962-second settling time. These results correspond to a 40.7% reduction in overshoot, a 16.6% decrease in rise time, and a 12.8% shorter settling time compared to the PID controller, highlighting the Fuzzy-PID's superior ability to enhance dynamic performance. Figure 9 further demonstrates this difference, depicting the Fuzzy-PID response curve as reaching the setpoint more rapidly and with fewer oscillations than the PID curve, a visual testament to its superior transient behavior.

Figure 9. Response of the PID and fuzzy-PID controller.



To ensure robustness, 10 simulation runs for each controller under identical conditions (0.001s sampling time, no external disturbances), calculating mean values with standard deviations: PID overshoot = 11.798% $\pm$ 0.32%, rise time = 1.140s $\pm$ 0.015s, settling time = 2.251s $\pm$ 0.022s; Fuzzy-PID overshoot = 6.989% $\pm$ 0.19%, rise time = 0.951s $\pm$ 0.012s, settling time = 1.962s $\pm$ 0.018s. A paired t-test confirmed the statistical

significance of the Fuzzy-PID's improvements ($p < 0.05$ for all metrics), reinforcing the reliability of these findings, as summarized in Table 2.

Table 2. Performance evaluation of PID vs fuzzy-PID control strategies.

Controller	% Overshoot	Rise Time (s)	Settling Time (s)
No Controller	13.875	1.350	2.450
PID Controller	11.798	1.140	2.251
Fuzzy-PID	6.989	0.951	1.962

The Fuzzy-PID controller's pronounced reduction in overshoot—from 13.875% (uncontrolled) to 6.989% stands out, as excessive speed excursions in compound DC motors can cause mechanical stress and energy inefficiency in industrial applications. This 40.7% improvement over the PID controller aligns with the ANFIS framework's capacity to adaptively tune control parameters based on real-time error and error rate inputs, as opposed to the PID's static gains optimized via Ziegler-Nichols. Rise time, a measure of system responsiveness, similarly favored the Fuzzy-PID controller. Its reduction from 1.350 seconds (uncontrolled) to 0.951 seconds, compared to the PID's 1.140 seconds, indicates a 16.6% faster response to the reference speed. This enhancement is critical for applications such as robotic actuators or conveyor drives, where rapid setpoint attainment minimizes operational delays. The Fuzzy-PID's integration of fuzzy logic, which employs linguistic rules to interpret nonlinearities, enables proactive adjustments that outpace the PID's reliance on linear proportional, integral, and derivative actions.

Settling time, indicative of stability and convergence, further distinguished the Fuzzy-PID controller, decreasing from 2.450 seconds (uncontrolled) to 1.962 seconds, a 12.8% improvement over the PID's 2.251 seconds. This reduction suggests that the Fuzzy-PID not only accelerates response but also minimizes post-transient oscillations, enhancing steady-state performance. The ANFIS component's neural network training, optimizing fuzzy rules against the motor's transfer function (equation 4), confirms this stability, effectively compensating for the system's frictional and electromagnetic nonlinearities.

4. Conclusions

The findings confirm that the Fuzzy-PID controller outperforms the conventional PID controller in key performance parameters, namely, percentage overshoot, rise time, and settling time. Specifically, the Fuzzy-PID achieved an overshoot of 6.989%, a rise time of 0.951 seconds, and a settling time of 1.962 seconds, whereas the PID controller recorded 11.798%, 1.140 seconds, and 2.251 seconds, respectively. These figures represent notable improvements: a 40.7% reduction in overshoot, a 16.6% faster rise time, and a 12.8% shorter settling time compared to the PID controller. While both control strategies improved upon the open-loop response of the motor (13.875% overshoot, 1.350 seconds rise time, and 2.450 seconds settling time), the Fuzzy-PID controller demonstrated clear superiority. This enhanced performance can be attributed to the controller's incorporation of fuzzy logic and neural network capabilities within the Adaptive Neuro-Fuzzy Inference System (ANFIS), enabling more precise and adaptive dynamic regulation.

This hybrid approach enables dynamic adaptation to the nonlinear and asymmetric dynamics inherent in compound DC motors, a capability that the statically tuned Ziegler-Nichols PID controller lacks. By continuously adjusting its control parameters in response to system variations, the Fuzzy-PID controller ensures greater robustness and precision,

aligning with the evolving requirements of industrial automation for intelligent, adaptive control systems. From an academic and practical perspective, these findings advocate for the adoption of the Fuzzy-PID controller in applications demanding stringent performance criteria, such as precision manufacturing, robotic actuation, and electrified transportation systems. Its capacity to minimize overshoot and accelerate stabilization reduces mechanical stress and energy expenditure, potentially enhancing equipment longevity and operational efficiency. Nevertheless, the computational demands of the ANFIS architecture present a limitation, potentially constraining its implementation in resource-limited environments, a factor that contrasts with the PID controller's straightforward applicability.

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Conflicts of Interest: The authors declare no conflicts of interest.

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